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Content

Introduction

Urbanisation processes are results of a broad variety of actors or actor groups and their behaviour and decisions based on different experiences, knowledge, resources, values etc. The decisions done are often on a micro/individual level but resulting in macro/collective behaviour. In urban research the 'city' as subject of interest is increasingly understood as a complex system because of these complex relations and interactions of actors, with no coherent delineation, somehow robust and steady, but also dependent on many factors which are almost of no individual importance but might have a strong influence on the bigger system. Traditional scientific methods or theories often tried to simplify, not accounting complex relations of actors and decision-making. The introduction of computers in simulation made new approaches in modelling, as for example agent-based modelling (ABM), possible, dealing with issues of complexity. Also in urban research, computer simulation is becoming popular for more and more issues, aiming at a new understanding of urban systems.

The essay is structured in two chapters. In the first chapter I summarize contemporary views on complexity in science and how it is understood in urban research. It seems that two related issues are relevant for urban research: First the question of the development of urban systems out of the interactions and decisions done by the inhabitants; second the question of planning or steering these systems; who are the decision-makers and how do they interrelate. Both questions are closely related one to the other.

In the second chapter I will focus on ABM as an approach to simulate, analyse and explain complex systems. After introducing ABM and locating it within the development of simulation in social sciences, some possiblities for applications of ABMs are discussed and a summary of evaluations of the ABM approach is given. Finally some open questions are discussed and the concepts are set in relation to my further work on my PhD project.

The essay is based on some recent articles as well as some relevant websites. Due to the use of ABM in many scientific fields and the relevance of complexity for a majority of science, there exists a huge number of scientific articles, books, tutorials etc. to these topics which doesn't make it easy for a novice in the field to find the right literature. The literature used gives an optimistic outlook for the future of this methodology, although ABM is (still) seen very critical regarding its usefulness and explanatory power.

Urban complexity

Emergence of complexity

The concept of "complexity" is not new in science. Although much of contemporary research puts complexity in focus (e.g. issue of "Science" on complex systems, Vol. 284, 1999), the notion of complexity seems to be an issue already since the middle of the last century. However, the use of complexity as a theory as such appears not to have been implemented in certain fields of science as it could be assumed, mainly reflecting the complexity of the concept itself and the lack of fully developed methods and research tools.

Vicsek (2002) describes the emergence of complexity in science by a shift in understanding science. He writes that in the past reality was understood by simplification and analysis, ignoring a number of additional factors which might not matter much so it was possible to formulate models or idealizations of certain systems. This form of reduction might lead to wrong conclusions in complex systems. Complex systems are close to chaos, having sometimes regular behaviour but that also can change, if there are only small conditional changes. Because of that complexity, it is not possible to describe a complex system by the laws its individual units are behaving, as the laws describing the system's behaviour are different from them, requiring a new theory for the system.

Additionally, the social world is getting more complex. More people participate in decisions through democratisation and decentralization on various levels, globalisation and new technologies increases their interrelations and people become more diverse and individual through an increase in wealth. Hence, the emergence of complexity in science can be reasoned by two factors: A change in understanding the reality (e.g. systems like climate are more complex than we thought), and a change of the reality itself (e.g. systems like urban planning become more complex through the decentralization of decision-making processes). Moreover, the advancing of computational powers and the increased organization of data into databases at finer levels support the development of new approaches to study complexity.

Complexity and urban research

Already Jane Jacobs (1961: 433) emphasised the complexity of cities. She referred to Warren Weaver's essay (1948) and described cities to be *"problems in organized complexity […] They present "situations in which a half-dozen quantities are all varying simultaneously and in subtly interconnected ways." Cities […] do not exhibit one problem in organized complexity, which if understood explains all. They can be analyzed into many such problems or segments which […] are also related with one another."*

With the advancement of computers and modelling techniques the notion of complexity is finally also becoming a crucial issue in urban research. Batty (2005) writes that *"[s]ystems of cities are no longer thought as being "complicated" but rather "complex", in that there is always uncertainty about the outcome of the processes of change that originate from the bottom up. This is what we mean by "complexity"."* Further he writes in a later article (Batty 2008), that *"cities are the example par excellence of complex systems"*, as they are *"emergent, far from equilibrium, requiring enormous energies to maintain themselves, displaying patterns of inequality …"*.

While Jacobs and Batty identify urban complexity within the complex composition of a city and its development, Healey (2007) understands urban complexity from a slightly different perspective, more an urban planning perspective. According to her, urban systems were traditionally understood as coherent entities called 'cities', integrating all processes in these entities. Urban planning was an instrument to counteract the disordering of these systems. But nowadays she summarizes, cities and urban areas cannot be understood as integrated unities with a certain dynamic and boundary. The interactions of actors in multiple networks on different scales and levels create complex urban systems impossible to 'plan' with traditional methods.

Again there are two understanding towards explaining (and dealing with) complexity: (1) The need to understand cities as complex systems themselves and (2) the understanding of how to manage cities, moving from a top-down approach to a relational planning (Healey 2007) incorporating a broad range of actors in the process, enabling better results but at the same time making it a very complex process.

These two understandings require different approaches in research and practice. Healey (2007, 11) emphasises a 'relational planning' incorporating on the one hand the issue of governance and planning, trying to understand the relations of collective action shaping governance interventions. On the other hand, planning is itself a part of the urban system, related to all sorts of other dynamics and decisions shaping the future of daily life in urban areas. 'Relational planning' is therefore a product of, as well as it comes to have effect on urban systems. This understanding requires new approaches and tools dealing with decision-making, governance, participation and strategy-making.

In the following, I will focus on the first understanding of urban complexity and the necessity to develop tools to study complex urban systems and their development. Agent-based modelling claims to be a capable tool for that task.

Agent-based modelling and simulation

The emergence of complexity in science questions traditional methods and tools of research. New approaches are necessary to understand and study complex systems; one of them is agent-based modelling (ABM)[1]. ABM is used to study the behaviour and relations of agents in these systems and the patterns and results of macro behaviour. Its significance and usefulness of outcomes is widely discussed in various fields of science for some decades and especially since the wide availability of necessary hard- and software. ABMs are mainly used in ecology & biology and social sciences, simulating the behaviour of people, groups, organizations, social insects, swarms, herds or also collaborating robots. The applications deal with a broad range of topics like supply chain optimization and logistics, consumer behaviour, workforce management,

[1] There exist several synonyms for Agent-based modelling (ABM), e.g. Agent-based simulation (ABS), Agent-based modelling and simulation (ABMS), Individual-based modelling (IBM), Multi-agent systems (MAS)

residential segregation, group formation, social network effects, traffic congestion, spread of epidemics, growth and decline of civilizations, human immune system.

Locating agent-based modelling in social sciences

ABMs study systems which are composed of (1) interacting agents and (2) emerging properties, meaning properties which arise from the interactions of the agents that cannot be deduced by aggregating the properties of the single agents (Axelrod and Tesfatsion 2006). ABM seems therefore to be an important method for social sciences were it is necessary to understand individual behaviour but also how interactions of several individuals lead to a certain outcome, which can be more than the "sum of the parts".

Simulation in social sciences could be understood as a third domain, complementing both natural language and mathematical/statistical sociology (Halpin 1999). Also, simulation is mentioned as a third way of doing science in addition to deduction and induction (Axelrod and Tesfatsion 2006). In deductive reasoning a posted theory is narrowed down into a hypothesis which then is tested, trying to confirm the original theory. For inductive reasoning a specific observation is analysed, leading to the detection of patterns. A hypothesis can then be formulated, ending up with general conclusion or theory. Simulation, and so also ABM, differs from standard deduction and induction as it does not prove general theories, instead it generates data for inductive analysis. However, the simulated data does not come from direct observations of the real world, but from certain specified assumptions.

Gilbert and Toitzsch (1999, in Macy and Willer (2002)) describe ABM as the last of three approaches emerged during the development of social simulation:

- Macrosimulation (1960s), simulating control and feedback processes in organizations, industries, cities, global populations.
- Microsimulation (1970s), using representative samples of individuals representing behavioural processes, simulating evolution through time of individual.
- Agent-based models (1980s), using, unlike the socially isolated actors in micro-analytical simulation, agents that interact interdependently.

According to Macy and Willer (2002) the development of ABM reflects the *"growing interest in the possibility that human groups, like flocks of birds, may be highly complex, nonlinear, path-dependent, and self-organizing"*, in contrast to a traditional understanding of social life *"as a hierarchical system of institutions and norms that shape individual behavior from the top down"*. They conclude, that *"[w]e may be able to understand these dynamics much better by trying to model them, not at the global level but instead as* *emergent properties of local interaction among adaptive agents who influence one another in response to the influence they receive."*

Elements and concepts of Agent-based modelling

A written above, an ABM is a tool to study the behaviour of agents. It roughly consists of three elements (Macal and North 2005):

- A set of agents (part of the user-defined model)
- A set of agent relationships (part of the user-defined model)
- A framework for simulating agent behaviours and interactions (provided by an ABM toolkit or other implementation)

Agent-based models have not necessarily a spatial dimension; they could also be designed as a so called "soup" model[2]. However, most of the time they are integrated in a space in combination with cellular automata (CA), network-models or geographic information systems (GIS). CA-models consist of a regular grid of cells which change their status by a simple set of rules. A cellular automaton is not an ABM by itself but is used to study clustering within spatial networks. Thomas Schelling illustrated 1978 (Axelrod and Tesfatsion 2006;Halpin 1999;Macy and Willer 2002) in one of the earliest ABMs, combined with a CA, a model for neighbourhood segregation. Randomly distributed red and green agents move to empty locations if the number of agents of the same group in the neighbourhood falls below a certain threshold. The model shows that a high degree of residential segregation can emerge from the location choices of relatively tolerant individuals.[3]

Besides the basic elements and the integration of an ABM in a spatial environment, the crucial functioning of the ABM is related to the agents' properties, distinguishing ABM towards other forms of simulation. Macy and Willer (2002) name four key assumptions:

1. Agents are **autonomous** (self-organization)
   Patterns emerge from the bottom up, coordinated not by centralized authorities or institutions (although these may exist as environmental constraints) but by local interactions among autonomous decision makers. This process is known as "self-organization".
2. Agents are **interdependent** (each agent's decisions depend in part on the choices of others)

[2] In a soup-model no spatial reference is used, all agents are equally connected.

[3] A demonstration software of Schelling's model can be downloaded at http://www.econ.iastate.edu/tesfatsi/demos/schelling/schellhp.htm

Agents influence others in response to the influence that they receive. Interdependence may also be indirect, as when agents' behaviours change some aspect of the environment, which in turn affects the behaviour of other agents

3. Agents follow **simple rules**

   ABMs explore the simplest set of behavioural assumptions required to generate a macro pattern of explanatory interest. Global complexity does not necessarily reflect the cognitive complexity of individuals or as they write *"the apparent complexity of our behaviour is largely a reflection of the complexity of the environment."*

4. Agents are **adaptive** and backward-looking (memory)

   Agents adapt by moving, imitating, replicating, or learning, but not by calculating the most efficient action. They can adapt at the individual and the population level.

All four assumptions seem crucial for an agent-based approach. A further concept integrated in ABM as a result of the interdependency and the complexity of the systems is an event called "tipping point". Tipping points describe a moment when something previously unique becomes common or a development leads to irreversible change, in other words the possibility that a small event can cause a big change. The tipping point can also be observed in Schelling's model of neighbourhood segregation, when the number of neighbours of the same group suddenly becomes too low and results in migration of all other group members.

Agent-based modelling to simulate land-use change

Following the key assumptions on agents, Macy and Willer (2002) identify two major issues around most applications of ABM in social sciences are located:

a) The self-organization of social structure (**emergent structure**)

   In these models, agents and agent-behaviours move through social and physical space in response to social influences and selection pressures, include Schelling's residential segregation, density-dependent organizational survival, group formation, and cultural differentiation.

b) The emergence of social order (**emergent order**)

   These studies show how egoistic adaptation can lead to successful collective action without either altruism or global (top-down) imposition of control, simulating issues referring to trust and co-operation.

This categorization helps to get a broad overview over what ABMs are currently used for. In urban research ABMs dealing with land-use change, often called ABM/LUCC (Agent-based models of land-use and land-cover change)[4], are a widely used form of ABM. These models combine agent-based representations of decision-makers influencing a land-use system with a cellular landscape on GIS-basis and are suitable when complex dynamics are present (Parker 2005). To get an overview of ABMs focusing on land-use change, Matthews et al. (2007) reviewed some applications and which can be categorized into 5 areas, some applications falling into more than one area:

- Policy analysis and planning
- Participatory modelling
- Testing hypotheses of land-use and settlement patterns
- Testing social and economic science concepts
- Modelling landscape functions

I will not go into detail with applications referring to these 5 issues as they are quite well and graspable explained by Matthews et al. (2007). Still, I want to give a short summary of the paper over the usefulness of ABMs in these areas. ABMs in the area of policy analysis and planning seem so far not to be used by policy-makers or planners, showing a lack of outreach and communication. On the other hand, ABMs with a participatory approach are not only subject to a discussion of results but also the structure of such an ABM is an output of the process limiting its application to a certain situation. The focus on testing hypotheses of land-use and settlement patterns seems useful to providing greater insight into actual processes involved in land use while models focusing on testing social and economic science concepts, so far, were used to compare other modelling approaches. Only a few examples deal with the modelling of landscape functions. However, this approach seems quite important as it investigates the linkages between human behaviour and biophysical processes in the landscape.

Summarizing from the examples, Matthews et al. (2007) identify three major advantage of ABM/LUCCs with the final aim of developing principles for managing real coupled human-environment systems:

1. Modelling of individual decision-making entities, considering interactions between them, and linking micro-scale decisions to macro-scale phenomena
2. Incorporation of social processes and non-monetary influences on decision-making
3. Linking social and environmental processes and providing a way of studying human-ecosystem relationships

[4] ABM/LUCC is sometimes also called ABLUM (Agent-based land-use model) or MASLUC (Multi-agent system models of land-use change).

Evaluation of the Agent-based modelling approach

The tenor of evaluations on the significance and usefulness of ABM is relatively similar in the literature used. An important issue to consider regarding the relevance of ABM seems the connection to the empirical world and to contemporary social theory. O'Sullivan (2004) notes the problem that the current methodology of ABM requires, that researchers decide what is important enough to be presented in a simulation and what not. Clear standards are necessary to be aware of model constraints and the significance of results. Nevertheless, he argues that ABMs are powerful tools, having much to offer for research. A similar weak point of computer simulation raises Moretti (2002). She points out the differences of virtual worlds from the real world it is referring to, and that each verified behaviour is also a deduction of the theory from which the model derives.

Macy and Willer (2002) emphasize that certainly not all problems are useful to be viewed from the bottom up as in ABM. The most appropriate applications study *"processes that lack central coordination, including the emergence of organizations that, once established, impose order from the top down."* ABM seems helpful and can contribute to theory when the results on the macro level are more than the aggregation of individuals and the macro behaviour cannot be understood without a bottom up view.

Parker (2005) notes that ABMs used to simulate land-use change is still a young but rapidly developing field. She emphasizes that it would be important to develop a shared vocabulary and understanding by developing a standard generic ABM/LUCC modelling framework. There are a large number of projects being developed, but using a different framework hampering the necessary coordination between researchers.

Matthews et al. (2007) see the prime challenge of ABM research to provide new insights into complex systems which traditional approaches have not delivered yet. The greatest use of ABMs so far has been for researchers to organise knowledge from empirical studies or to explore certain theoretical. They point out that the connection to real world problems might rather be simple rules-of-thumb than operational decision support tools.

The most discussed issue seems the integration of theory and empirical results into simulations. This would move ABM from its scientific "game" image to an equally considered scientific approach. However, there is a general optimistic perspective for ABMs in all literature used, quoting a promising outlook for the approach.

Discussion

The issues of complexity as well as of computer simulation in social sciences are certainly of a high relevance in urban research, but also sciences in themselves. The notion of complexity in urban research is partially quite different defined and approached. Nevertheless, there is a consensus on the need of such new approaches facing today's developments and challenges in cities and planning. Agent-based modelling still has a certain scientific 'game' touch. Currently the usefulness of ABM depends very much on its kind of application. It seems to have a higher significance as explanatory tool than for predictive purposes.

The extent of this essay is relatively little for topics like complexity or agent-based modelling and simulation. This essay offered a small insight into a huge research field. However, the aim was to gain some insight into these issues and the current research, which is developing quickly with the advancement of computing hardware and the development of capable and accessible software, allowing more and more researchers to apply these techniques. Certainly, through the work on this essay several further issues arose which could not be covered:

- A deeper understanding of complexity and its location in science and urban research. The book of Peter Allen (1997), which was not available to me during the work on the essay, might give further insights.
- The approach of 'relational planning' (Healey 2007) to deal with complexity in planning
- The use of social theory in ABM applications
- The significance and explanatory power of other forms of computer simulation in urban research as e.g. cellular automata
- The concrete application of ABM, how does it work technically and is it worth the effort (for a 'non-expert')

However, they might not be followed up as their relevance to my PhD project is (currently) relatively low on a detailed degree. In my project, dealing with effects of urbanisation processes and relationships in the urban periphery, no particular focus on behavioural and individual decision-making theories is put so far. Nevertheless, the understanding of the city as complex system is very relevant. Out of the issues discussed in the essay following interfaces to my further PhD work can be imagined:

- *Relational planning approach*

  Although this approach was not further discussed in this essay, it should be taken in consideration for a later phase in the project at a possible focus on spatial planning strategies.

- *Principle concepts of collective behaviour (self-emergence, tipping points…)*
  Concepts of collective behaviour might be an input to hypotheses for processes in peri-urban areas.
- *Simulating and modelling*
  Simulation and modelling should be considered as an approach to explore certain patterns of peri-urbanisation in a case study region or evaluate scenarios. However, an ABM seems to complex for my tasks, therefore it will be necessary to find more appropriate alternatives.

Certainly to pick up from this essay for further work is the emphasis on differentiated methods to understand complex systems. Statistical analyses of variables have to be seen in this perspective and discussed for their concrete usefulness to illustrate complex relationships and problems as occurring in cities. Urbanisation processes are results of a broad variety of actors or actor groups and their behaviour and decisions based on different experiences, knowledge, resources, values etc. This complexity has to be considered when using certain analysis methods to avoid simplification.

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Some internet resources related to Agent-based modelling

http://backspaces.net – Tutorials, software etc.

http://ccl.northwestern.edu/netlogo/models - Platform for 'simple' models, many examples

http://www.geosimulation.org – Articles, lectures

http://mason.gmu.edu/~dparker3 – Articles, lectures

http://www.econ.iastate.edu/tesfatsi/abmread.htm - Guide for newcomers, articles

http://gisagents.blogspot.com – Blog on ABM & GIS

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